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13. ABSTRACT (Maximum 200 words)

Brain activity was recorded with microelectrode arrays permanently implanted in the cerebral cortices of rhesus monkeys. The recorded activity was extracted in real time and used to control an anthropomorphic robotic arm. In the initial task, the monkey used this arm to reach out and grasp a piece of food and return it to its mouth by operating a simple gripper at the end of the arm. More recently another monkey is operating the arm in a doorknob task with the goal of reaching, grasping, twisting and pulling. The arm is now outfitted with a 4DOFarm, a 3DOF wrist and a 4DOF hand. We have developed algorithms to extract wrist orientation, trained the subject to perform hand orientation using brain control and the newly-installed wrist and demonstrated this in the task.

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Enclosure 1

The two main goals of this project were to; 1) Describe the way neurons in the motor cortex encode the posture of the wrist, hand and finger during reach-to-grasp, and 2) Demonstrate the control of an anthropomorphic arm and hand using brain-control in a task where a robot arm reaches out grasps, twists and pulls a doorknob. We have made a good deal of progress toward these goals. The major advances we have made in this reporting period include recordings from behaving primates that now include EMGs from arm muscles in addition to cortical neural activity and hand kinematics and the addition of a 3 DOF wrist to our robot control experiments. This allows the hand to be oriented to the grasp object and is a major advance in prosthetic control.

Neurophysiological results-

Monkeys were trained to reach out and grasp an array of objects placed in their extra-personal space with a robot arm.   Joint angles from the 23 degrees-of-freedom of the wrist and hand were precisely measured by tracking passive markers on a glove and sleeve worn by the monkeys. Single-unit action potentials were recorded from 5 electrodes placed in the motor cortex. In a recent enhancement, muscle activity from 13-16 implanted EMG electrode pairs is also being recorded simultaneously with the other data.

Database
We have recorded more than 1600 units from five hemispheres of three monkeys performing more than 120,000 trials. These data were used to characterize the relation between neural activity and hand kinematics. In summary, the 23 DOF used to describe hand shape could be grouped into 8 eigen postures which together accounted for more than 85% of the overall variance. Many of the single neural activity had significant regressions to the 23 DOF. The same neurons also tended to have significant regressions to the principal component space, suggesting that the more efficient mapping is well represented in M1 cortical activity.

EMG-neural studies have been carried in two monkeys in which a total of about 300 units were recorded in conjunction with chronic EMG recordings of 13 muscles of the hand and arm and the corresponding kinematics from recorded position data.
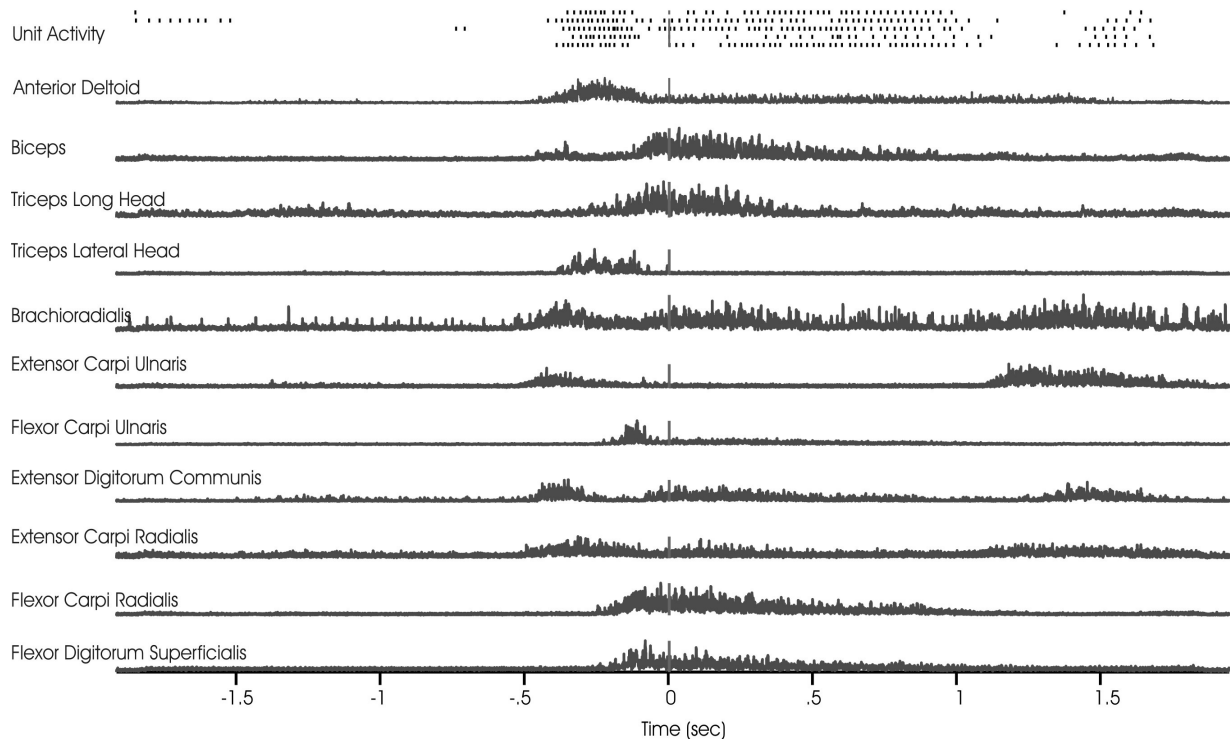
Unit and rectified EMG data from five repeated trials to the same object. Trials were aligned (vertical bar) to object contact which lasted about 1 second.

Spike-triggered averaging (STA) is an important analytical technique to better understand the relation between motor cortical and muscle activity (EMG). A snippet of EMG data (e.g. 20 ms) is collected after each cortical spike and then averaged together across spikes. The resulting averaged, pattern typically has a post-spike facilitatory profile if the neuron is acting as an EMG driver. The problem with this technique is that the probability of any given cortical spike causing a change in EMG is very small, so that a large number of samples is needed and this is difficult to do in our experimental paradigm. For this reason, we have developed a number of STA enhancements.

STA enhancements

Template matching
One way to increase STA efficiency (demonstration of post-spike event with fewer trigger events) is to use template-matching which works by counting the number of times the post-spike waveform matches a template. Based on the assumption that post-spike effects occur only rarely in the target EMG, averaging will tend to erode the post-spike profile in the absence of a spike. This does not happen with template methods.
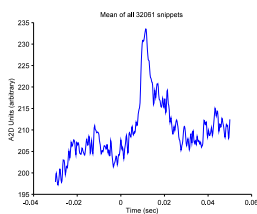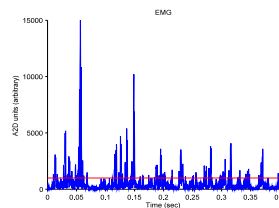

Figure 2
Conventional STA

Figure 3
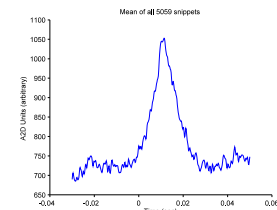Rectified EMG
showing threshold

Figure 4
STA of thresholded
snippets

An approach using template-matching, was developed to detect the shape of the post-spike effect for a single neuron-muscle pair. A cortical neuron-muscle pair with a significant facilitatory post spike effect, as detected by conventional STA, was used (Fig. 2). These data were recorded during a single digit movement experiment and 32061 Spike triggered snippets were extracted from the EMG time series (data courtesy of Dr. Marc Schieber). These snippets were thresholded and only snippets containing EMG values above a low threshold were kept. This threshold was chosen so snippets with no EMG activity or background noise were eliminated (threshold example in Fig. 3). The spike triggered average (STA) of the remaining 5059 snippets is shown in figure 4 and it can be noted that a lot of the background noise was eliminated and the amplitude of the average increased.
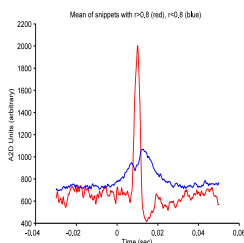

Figure 5
STA of good matches (red)
vs STA of poor matches
(blue)

A template matching procedure was then employed, where a Gaussian bump with a 2 ms width was used. This was meant to detect any isolated action potentials following the cortical spikes. The cross correlation between every snippet and the template was computed and the highest cross correlation value in the range of 6-16ms post spike was retained. Of all the 5059 snippets, only 555 snippets had good matches to the template (the threshold used was r>0.8). The STA of the snippets with good matches to the template is compared to the STA of the snippets where the template did not match well in figure 5. This STA can be used, for example, as a starting value for the PSE in the main model. The fact that only one in every 58 spikes shows a good match to the template and that the STA computed from those spikes accounted for the majority of the amplitude in the original STA demonstrates how weak functional connectivity

can be. Even for a monosynaptic connection, only 2% of the spikes produced a post spike effect. As validation, the spike train and EMG time series were split into segments and were sampled with repeats. The template matching was then carried out on the shuffled data and the matches with correlation above .8 were counted. This was repeated 1000 times and the maximum number of matches was 73 (mean = 48). The 95% confidence interval for the bootstrapped data was at 56 matches showing that the 555 matches were much beyond that expected by chance.

Figure 6 Match-triggered firing rate histograms
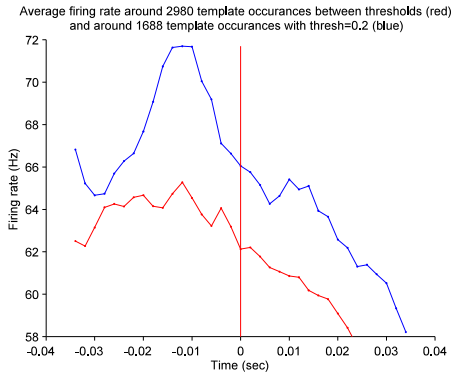
In addition, this approach was used to estimate the firing rate of the cortical neuron around times where the template occurred in the EMG. Instead of performing the matching on snippets, the Gaussian bump was shifted throughout the whole EMG time series.   A firing rate histogram of the cortical neuron (Fig. 6) around the good matches (blue, r > .2, n=1688) shows both a broad modulation a second before the match and a sharper increase about 30 ms before the match decreasing to a low rate 35 ms later. Weaker matches (red, .1<r<.2, n = 2980) showed only a broad modulation. This is an indirect indication of the type of modulation in this neuron that tends to lead to EMG facilitation.

BCI-robot results-

To develop control of the more complex device, we have first extended the tuning model used for demonstration of a brain-controlled robotic self-feeding task to the control of orientation and hand shape. Then, we have developed a systematic method for governing the interaction between decoded cortical control commands and robot movement that provides a consistent decoding and training paradigm. We added terms for wrist orientation (yaw, pitch and roll), grip aperture, and hand shape to the classic regression formula used for 3D reaching.

At the beginning of a daily experiment we fit this equation using observation-based learning. The robot arm is moved through the task while the monkey watches. At the end of the task, the monkey is rewarded. The important result is that many neurons in the cortex are modulated throughout this observation and we determine each neuron's preferred direction with this modulated activity according to our calibration model.

Calibration Model - Virtual Directional Tuning

$$\Phi_i = \boldsymbol{\beta}_i \cdot \boldsymbol{\nu}^T + \epsilon$$
$$\boldsymbol{\nu} = \begin{bmatrix} \nu_x, & \nu_y, & \nu_z, & \nu_{yaw}, & \nu_{pitch}, & \nu_{roll}, & \nu_{grip}, & \nu_{shape}, & 1 \end{bmatrix}$$
$$\boldsymbol{\beta}_i = \begin{bmatrix} \beta_{ix}, & \beta_{iy}, & \ldots, & \beta_{i,shape}, & \beta_0 \end{bmatrix}$$

Regression coefficients β are determined from the set ν of observed robot movement parameters. A directional tuning model used previously for 3-D device control is extended to describe the encoding of non-Cartesian controlled variables. Control inputs that describe hand orientation and shape are treated as virtual directions orthogonal to 3-D directional movement.

Once we fit each cell's preferred direction. We switch experimental modes so that the recorded signal is now

controlling the robot motion. The control signal is formed using the classic population vector algorithm and is represented in a single high dimensional vector that contains the same dimensions as those used in the calibration model.

Prediction Model

$$v_* = \alpha \sum_t \beta_{t*} \varphi_t$$

The prediction model used is a high dimensional version of the Population Vector Algorithm. Summation of individual unit preferred directions supplies a control signal in real and virtual directions. An automated system provides movement commands to the robot in real time.

Collaborative Control for BCI

One of the major advances we have made in this last reporting period is the formalization of training procedure that uses shared-mode control to provide assistance to the subject during BCI training. This assistance is both passive and active.

In the active mode, an automated system provides movement commands to the robot in real time. Control commands derived from the monkey cortical implant are mixed with signals from the automated controller. This system provides a substrate for observation-based learning and enables learning the control of individual degrees of freedom on an incremental basis while ensuring task completion.

In the passive mode, the monkey's brain control signal is attenuated for an individual DOF if the control signal would move the limb outside a "desired command region."   The amount of attenuation is adjustable and is reduced as the subject learns to operate the device to keep it in the proper region.

$$\mathbf{V} = \mathbf{C} \left([\mathbf{D},\mathbf{U}]^* + \mathbf{C}_t \langle \mathbf{D},\mathbf{U} \rangle^* \right)\mathbf{U} + (\mathbf{I}\text{-}\mathbf{C})\, \mathbf{D}_1$$

$$\mathrm{PosSpan}(\mathbf{D}, \mathbf{U}) \equiv [\mathbf{D}, \mathbf{U}]^* = \begin{cases} \mathbf{D}(\mathbf{D}^T\mathbf{D})^{-1}\mathbf{D}^T & \mathbf{W} = \mathbf{D}^T\mathbf{U}, \forall i\ \mathbf{W}_i \geq 0 \\ \mathbf{0} & otherwise \end{cases}$$

$$\mathrm{PosKernel}(\mathbf{D}, \mathbf{U}) \equiv \langle \mathbf{D}, \mathbf{U} \rangle^* = \mathbf{I} - [\mathbf{D}, \mathbf{U}]^*$$

U is an m-dimensional vector of monkey commands. Columns of **D** are basis vectors of a "desired command region" supplied by an on-line grasp planning system. $\mathbf{D}_1$ is an m-dimensional matrix assumed to represent a command directly toward an optimal robot state. **C** is an m × m diagonal matrix, its nonzero elements representing an "operator command fraction" for each degree of freedom. $\mathbf{C}_t$ is an m × m diagonal matrix, representing anisotropic compliance in undesired command directions. **V** is the output command sent to the robot.

Our initial effort focused on the control of Cartesian hand location and pinch gripping. In the past year we have
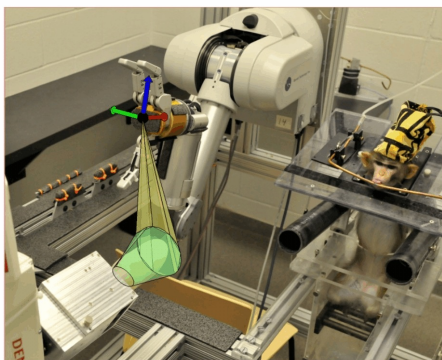

Shaded volume shows the desired control region of the control space in the context of the door knob task

extended this control to wrist orientation.   A rhesus monkey was implanted with dual "Utah" microelectrode arrays in the M1 arm and hand areas. Upwards of 100 isolated units on the 192 available channels are used for brain control.
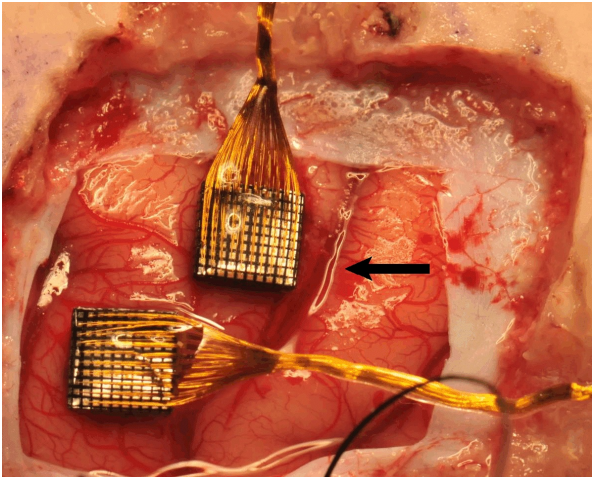

Full control of subsets of 7 degrees of freedom of the device, including direction, orientation, and grasp aperture, has been demonstrated. The maximum simultaneous control reached thus far is full 4-DOF control, with partial control over a 5th dimension.

Placement of two recording arrays in motor cortex. The arrow points to the central sulcus.
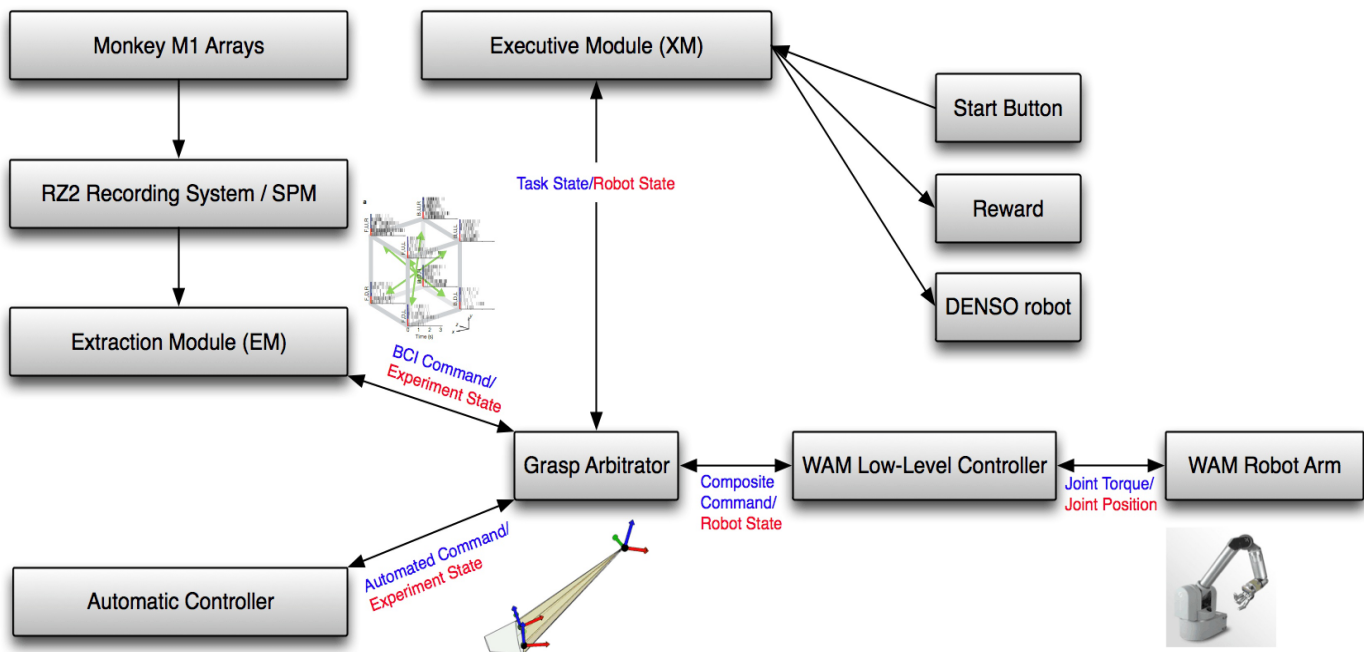
Task schematic- Signals recorded from two arrays are processed by an extraction module to generate the monkey's control signal. During training, this is mixed with an idealized control space generated by an automatic controller in the grasp arbitrator. The mixed signal is sent to the prosthetic arm/hand controller. The behavioral task is controlled by an executive module. All modules run simultaneously in our custom software environment.
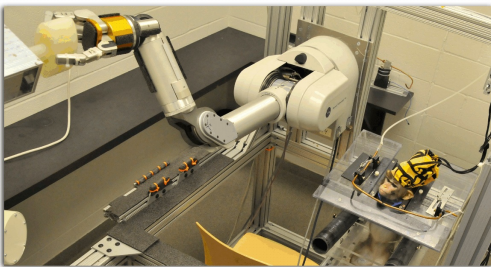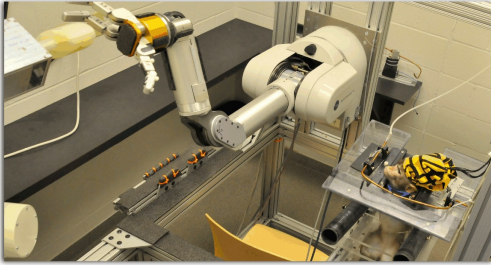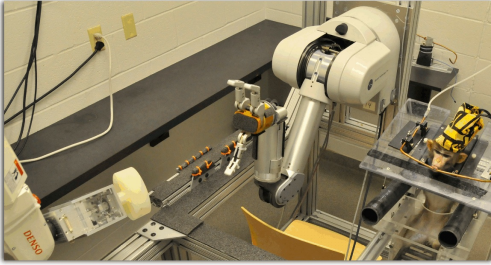
Sequence of events during a brain-control task requiring 5 control degrees of freedom from the monkey-computer system. The task shown here was to reach for the doorknob, rotate the hand to match knob orientation, and perform a grasp of the object.

Individual components (transport, orientation, hand shaping and grasping) of the task have been demonstrated separately. We are now working to carry out the entire task sequentially with a single control scheme.